

The Sources of Risk Spillovers among U.S. REITs: Asset Similarities and Regional Proximity

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Abstract

In this paper, we estimate the risk spillovers among 74 U.S. REITs using the state-dependent sensitivity value-at-risk (SDSVaR) approach. This methodology allows for the quantification of the spillover size as a function of a company's financial condition (tranquil, normal, and volatile REIT prices). We show that the size of risk spillovers is more than twice as large when REITs are in financial distress and find evidence for the impact of geographical proximity: REITs that have their properties located in close distance to the properties of other REITs show risk spillovers that are on average 33% higher than REITs that have similar properties but at a larger distance. We estimate the risk gradient to decrease nonlinearly and to have zero slope for property distances of more than 250 miles. Our empirical findings provide first empirical evidence on the transmission of risk spillovers from underlying real positions to the securitized level of a company. Specifically, our results highlight the relevance of geographical diversification for REITs and have important implications for the investment and risk management decisions of real estate investors, mortgage lenders, home suppliers, and policy makers.

Keywords: REITs, fundamental value, geographic diversification, information diffusion, risk spillovers, state-dependent sensitivity VaR (SDSVaR).

JEL-Classification: G01, G10, R12

1 Introduction

Risk managers in the real estate industry during the 2007-09 financial crisis were confronted with unanticipated risk spillovers among real and financial assets of unprecedented scale. In this paper, we propose a state-dependent sensitivity value-at-risk (SDSVaR) for quantifying risk spillovers among 74 U.S. Real Estate Investment Trusts (REITs). We explicitly account for the financial condition of a company during shock exposure. We show that size and persistence of these spillovers differ significantly for tranquil, normal, and volatile periods of real estate stock prices. Thereby, we are able to identify the direction of spillover effects from one REIT to another. In contrast to other publicly traded companies, REITs share a distinct spatial component in their fundamental value that impacts risk spillovers. We explicitly account for these spatial characteristics of REITs' property holdings. Due to their particular legal constraints and their straightforward business operations REITs provide, compared to industry companies, an interesting laboratory to test how spatial proximity in the underlying properties and asset similarities increase risk spillovers on the stock level.¹

A number of recent studies have investigated time-varying correlations among securitized real estate investment companies, in particular REITs.² These studies generally verify two stylized facts that have been already documented in the stock market literature: (i) correlations among equity markets vary considerably through time and (ii) stock market

¹ REITs generate almost their entire income from selling, managing, and owning real estate whereas the company value of many other firms is more related to human capital or to products that are movable and hence do not exhibit a certain geographical characteristic. In contrast, the value of a REIT is closely linked to the value of its properties and is much easier to measure than the fundamental value of industrial firms. The underlying properties of REITs can be valued almost precisely by appraisers based on the information such as property's income, age, quality, size, location, as well as transactions in comparable properties in neighboring regions and the recent past (Patel, Pereira, and Zavodov, 2009).

² Securitized real estate investment companies mainly consist of REITs, but also include listed property stocks and real estate operating companies (REOCs). In this study we will, however, focus on REITs only.

correlations increase in periods of high volatility (e.g., Bailey and Stulz, 1990; Bekaert, Harvey, and Ng, 2005; Solnik, Boucelle, and Le Fur, 1996; Goetzmann, Li, and Rouwenhorst, 2005). For instance, Chen and Liow (2006) investigate the transmission of volatility among the major REIT markets and find that volatility spillovers are more pronounced within Asian economies. Cotter and Stevenson (2006) investigate risk spillovers among daily returns of equity, mortgage, and hybrid REITs but find little evidence for the existence of spillovers. Elyasiani, Mansur, and Wetmore (2008) find shocks to REIT volatility to spill over to the market of other financial institutions such as savings and loan associations as well as life insurance institutions. These findings have important implications for the diversification potential of REITs in a traditional stocks and bonds portfolio. In the present study we contribute to this literature in three important ways.

First, our focus is on risk spillovers rather than return correlations. This shift in perspective from diversification to risk management comes with a subtle but important change in the way our results can be interpreted. In contrast to time-varying correlation models that simply measure the non-directional co-movement between assets, our spillover estimates not only quantify the size but also the direction of the spillover. We thereby control for other relevant factors such as general market movements in order to give our results a causal interpretation.

Second, we account for an important lesson of the 2007-09 financial crisis: the size of risk spillovers depends significantly on the market state or financial condition of a firm (see, e.g., Adrian and Brunnermeier, 2011; Brownlees and Engle, 2011; Acharya et al., 2010).³ This issue has also become the focus in recent studies in the real estate literature (see, e.g., Miao, Ramchander, and Simpson, 2011; Zhu, Füss, and Rottke, 2011). We address this issue

³ A few studies have investigated this asymmetry in spillover behavior even before the 2007-09 financial crisis (see, e.g., Bae, Karolyi, and Stulz, 2003).

in a state-dependent sensitivity value-at-risk (SDSVaR) model that allows us to discriminate between various conditions of financial health of a firm. We thereby model the risk spillovers for different quantiles of a REIT's risk distribution directly rather than splitting the data in two or more samples. This has the advantage of retaining the full sample size while addressing risk spillovers in the tails of the distribution. We find risk spillovers to increase substantially when the stock prices of the REIT that is exposed to a shock are in a volatile state.

Third, we incorporate a crucial feature that distinguishes REITs from other publicly listed companies: The spatial aspect of the properties owned by the REIT. A large body of literature documents the importance of local economic conditions on property prices. For instance, Meen (1999) concludes that the national housing market can be described by a series of interlinked local markets.⁴ Meen explains the observed linkages by investor behavior, consumer behavior, and interlinked economic bases. Higher house prices in one region create incentives for investors to buy homes in nearby regions that did not experience this house price increase.⁵ This would result in spillovers and diffusion of the initial house price increase. Furthermore, house prices in two regions are linked if lower prices in one region attract more migration flows than the other region. In a study for the U.K. housing market, however, Meen (1999) reports that migration flows are weak and points to empirical work showing that migration flows are not much influenced by regional house price differences (Gordon, 1990). Finally, even if housing markets are not directly linked there may be underlying local characteristics such as employment and income levels that may

⁴ Although most studies use data for single family houses (see, e.g., Cromwell, 1992 and Pollakowski and Ray, 1997 for the U.S. market and MacDonald and Taylor, 1993 and Alexander and Barrow, 1994 for the U.K. market) the spatial aspect extends directly to all property types.

⁵ Rising house prices also create concurrent wealth effects for existing homeowners, again generating incentives to invest in the housing market of the lower priced region (Miao, Ramchander, and Simpson, 2011).

themselves be linked interregionally leading to dependencies in housing markets across regions. This effect is the focus in a U.S. study of Coulson, Liu, and Villupuram (2010) who show that local employment and house prices are significantly driven by certain locally concentrated industries. For instance, the automobile industry is relevant for house price changes in Detroit while high technology plays a crucial role for the economic bases of Seattle and San Jose. Other studies that focus on the link between local economic bases and housing prices are Abraham and Hendershott (1996), Malpezzi (1999), and, more recently, Zhu, Füss, and Rottke (2011). Since the basic model of spatial equilibrium in urban economics predicts that owner-occupied housing and income-producing properties are driven by common fundamental (demand) sources (see, e.g., Rosen, 1979; Roback, 1982), we can assume that similar linkages exist for commercial real estate (see also Gyourko, 2009).

The issue of interregional linkages is also relevant for the present study on risk spillovers among REITs. Figure 1 shows the quarterly NCREIF property indices (NPI) for selected U.S. states from 2000Q1 – 2011Q3.⁶ The NPI consists of a large pool of commercial real estate properties that are acquired for investment purposes only. According to the information by NCREIF, the NPI consists of properties that have been acquired, at least in part, on behalf of tax-exempt institutional investors with pension funds being the great majority. As such, all properties are held in a fiduciary environment. Property prices in one state show a high degree of co-movement with property prices of neighboring states and, at the same time, a high degree of heterogeneity with property prices of states in other regions. For instance, on the West Coast, property prices show the strongest reaction, both in terms of a buildup in prices but also in the severity of the subsequent burst of that bubble during the 2007-09 financial crisis. To a lesser extent, this behavior is also visible for property prices in

⁶ The NPI is based on reported information about properties held by members of the National Council of Real Estate Investment Fiduciaries (NCREIF). In 2011Q4, the total market value of all 6,865 properties within the NPI was USD 283,762.4 million.

the North East. All four U.S. states in this region move closely together over time but on a smaller scale than comparable price movements in the West Coast area during the same period. In a similar manner we find commercial real estate prices in other regions like the South East or Midwest to show synchronized movements within a group of states but diverging price movements compared to other regions.

<<< Figure 1 about here >>>

Another strand of literature that has become particularly relevant after the subprime crisis of 2007 concentrates on spatial risk spillovers and externalities in the immediate neighborhood (Ioannides, 2003, Immergluck and Smith, 2006, Lin, Rosenblatt, and Yao, 2009, Harding, Rosenblatt, and Yao, 2009). In particular, Harding, Rosenblatt, and Yao (2009) show that the negative externality associated with deferred maintenance and neglect of a foreclosed property can lower house prices by 1% per nearby foreclosed property. In these types of studies the transmission mechanism of a foreclosed property is largely visual.

The high frequency of the daily REIT data allows for a more thorough investigation of risk spillovers. Recent studies acknowledge the large impact that varying economic conditions can have on risk spillovers. Miao, Ramchander, and Simpson (2011) model the “active phase” of the market using the time period 1999-2006 and a calm market phase from 1989-1998 and report substantially stronger linkages in the active phase. Zhu, Füss, and Rottke (2011) support these findings with a similar observation of increased co-movements among regional house prices during the 2007-2009 financial crisis.

Our approach in this study is to model the risk spillovers among 74 daily traded U.S. REITs for different quantiles of a REIT’s VaR distribution directly rather than splitting the data in two or more samples. This has the advantage of retaining the full sample size while addressing risk spillovers in the left tail of the distribution. The intuition behind this approach comes from the fact that large negative returns are contagious in a way that small negative

returns are not (Bae, Karolyi, and Stulz, 2003).⁷ Our results shed light on the importance of geographical diversification⁸ in real estate portfolio management and have important implications for the investment and risk management decisions of REIT investors, mortgage lenders, home suppliers, and policy makers.

In a further step, we investigate the determinants of the risk spillovers among the individual U.S. REITs but retain the locational characteristics of the underlying properties. In particular, we collect the exact geographical location of all properties held by each REIT to obtain a measure of geographical proximity between single REITs. We present estimates of the risk gradient which visualizes the increase in risk spillovers when the properties of two REITs are geographically close. In a parametric cross-sectional estimation, we also analyze the impact of balance sheet variables on the size of risk spillovers. These factors are found to be relevant for the increase in systemic risk among financial institutions.

The direction of the paper is as follows. In the next section we present a theoretical motivation for the transmission mechanism of shocks and the role of geographical distance. In section 3 we show how risk spillovers among single REITs can be modelled. Section 4 investigates the risk spillover estimates in a cross-sectional analysis and presents

⁷ Another methodological approach for modeling the tail dependencies between REIT markets has been proposed by Hoesli and Reka (2011). The authors use a time-varying copula framework and document different dynamics between tail dependencies.

⁸ In general, empirical studies on geographical (economic) versus sector-type diversification in direct real estate have found conflicting results. For example, while Miles and McCue (1982, 1984) emphasize the benefits from sector-type diversification, Hartzell, Hekman, and Miles (1986) and Grissom, Hartzell, and Liu (1987) find evidence that regional dominates sectoral diversification. Similarly, Hartzell, Shulman, and Wurtzbaach (1987) and Malizia and Simmons (1991) confirm that economic regions allow for a wider scope of diversification. In contrast, Eichholtz et al. (1995) stress the relative superiority of diversification by type and by region, because of the difficulty in generalizing for all regions or sectors in either the U.K. or the U.S. In a recent study, Lee and Devaney (2007) find that diversification effects in property types and geographic regions do not necessarily remain stable over time. For most periods, and especially when return volatility is high, sectoral diversification seems to be superior to region-specific diversification. In a recent study, SeungHan and Ziobrowski (2011) do not find superior performance for REITs specialized in a single property type.

counterfactual results using impulse response functions. The final section contains the conclusion.

2 The Mechanism of Risk Transmission from Direct to Securitized Real Estate

In this section we investigate possible risk transmission mechanisms as an attempt to explain empirically observed differences in some REITs' responses to exogenous shocks. We use the insights from this section to form expectations concerning the empirical results of this paper. Due to their straightforward nature of operations, REITs provide an excellent laboratory to analyze how specific fundamental information is incorporated into stock prices, and how shocks in the fundamental value transmit to the securitized level. We argue that the specific response of a REITs VaR depends on (1) the type of the exogenous shock and (2) the degree to which a REIT is vulnerable or exposed to a given type of shock.

We distinguish between three different types of shocks that lead to co-movements and risk spillovers among the stock prices of REITs. Two types of shocks are based on the fundamentals, i.e. property holdings of REITs, and one is due to stock market linkages. We subdivide on the fundamental level into national economic shocks and local economic shocks. National economic shocks affect all REITs in the country in a similar way. For instance, changes in interest rates—or expectations thereof—lead to changes in the value of property investments throughout the country. To the extent that investors in REITs react to the new information in a similar way, we therefore expect to see co-movements in REIT prices.

In contrast, local economic shocks are more relevant to some REITs than to others. For instance, an adverse shock in a concentrated industry like the automobile industry in Detroit is particularly relevant for REITs that own properties in that region. In such a case, we would expect to see spillovers between REITs through fundamental changes in the value and

income potential of properties. When the information on the regional economic shock diffuses into the market, investors will anticipate the future dismissals in the service sector as well as losses in rental income from residential properties. The selling of office and residential REITs will then be triggered by spillover effects from industrial and retail REITs. This is obvious because income-producing residential stock constitutes denser multifamily houses which are more likely to be located in the central city of a metropolitan area. To revisit the example from above, the closing of a car factory and the subsequent drop in purchasing power from layoffs in the supporting industry will have a direct effect on industrial and retail REITs. Over time, some workers will reallocate to other regions for a new job thereby increasing the supply of vacant residential properties. This will lead to sectoral spillovers from one type of REIT to another. A second example for spillovers due to a local economic shock would be a regional spillover. A drop in residential property values in the immediate area of the local economic shock dissipates to other nearby adjacent regions. In both cases however, the sectoral and the regional spillover constitute a propagation of risk from one REIT to another, similar to lending relationships between mutual portfolio holdings among financial institutions (Brunnermeier and Pedersen, 2009). In contrast, national economic effects are more likely to result in simultaneous co-movements of REIT prices. The degree to which one effect dominates over another is an empirical question and is investigated in section 4. The third type of shock is propagated via financial market linkages. This shock constitutes co-movements and spillovers that may be uncoupled from economic fundamentals and corresponds to the observation that short-run price movements of REITs are closely aligned with the general stock market (Glascock, Lu, and So, 2000).

Distinguishing between these three types of shocks, national economic, local economic, and financial helps to explain why risk spillovers may occur among some REITs but not among others. Other important factors in this regard, however, are the balance sheet

characteristics of the REITs themselves as they determine the degree of exposure of a REIT to the shocks in another. For instance, the profitability of a highly leveraged REIT is more sensitive to bad news such as lower than expected net operating income. Such a REIT may be therefore more susceptible to shocks from another REIT. By the same argument, the financial health of a REIT is likely to be an important factor. Consider a REIT that is under pressure from rapidly declining equity as a consequence of a series of failing property investments. This state of financial distress is reflected in highly volatile stock prices. In other words, the REIT has depleted its capital buffer to absorb any shocks and is highly vulnerable to any bad news. Under these circumstances, a shock in one REIT is likely to have a much higher impact on the distressed REIT than the same shock under normal or tranquil circumstances.

We summarize our arguments on how local proximity of property holdings and asset similarities affect risk spillovers among REITs in Figure 2. Panel A shows the different types of shocks on the fundamental and financial level. National and local economic effects influence REIT prices either directly or indirectly through future expected fundamental values. The volatility in the REITs' stock returns is furthermore driven by the balance sheet characteristics of the REITs as well as the state of their financial health. Panel B of Figure 2 shows how the individual risk channels add up to the observed spillovers among REITs and highlights the special role of distance as an indicator whether two REITs are exposed to the same or similar local economic shocks.⁹ For instance, general stock market linkages and national economic shocks affect all REITs in a similar manner whereas local economic shocks depend on the proximity of a REIT's properties to the affected region. Furthermore, we expect risk spillovers to shift upwards if the shock receiving REIT has above average leverage. Risk increasing characteristics accumulate. For instance, the risk spillovers are

⁹ Thereby, the distance between regions or districts is solely an indicator for the similarity or the dissimilarity in local economies

further increased if in addition to higher leverage, the shock receiving REIT is in a state of financial distress. From Figure 2 we draw two conclusions for this section: We expect risk spillovers to be higher for REITs that own properties in similar regions. However, we also expect to find positive spillovers between REITs without significant spatial linkages but with certain balance sheet and financial health characteristics which favour higher risk spillovers. The degree to which this is the case is an empirical question and will be answered in the following sections.

<<< Figure 2 about here >>>

3 Estimating Risk Spillovers: The Time-Series Setting

Our aim in this section is to estimate the risk spillovers between single REITs. Hence, we do not model the return distribution but instead focus directly on the REIT's daily risk. A risk measure that will be suitable for our approach is the value-at-risk (VaR). The VaR has the appealing property of expressing the risk in only one number. Its intuitive interpretation and regulatory importance has led to general acceptance and wide application for internal and external purposes.¹⁰ To illustrate the issue Figure 3 shows the VaR of the S&P U.S. general REIT Index over the time period 06/01/2007 to 03/16/2011 (956 observations). This period contains tranquil market phases as well as the highly volatile phase of the financial crisis which started to become visible in the REIT returns in mid 2008. Like most firms REITs experienced losses and strongly volatile stock returns during this period. This alternation of different periods presents an opportunity to investigate the risk spillovers during different market states. We will address this topic in more detail in the next section.

<<< Figure 3 about here >>>

¹⁰ For an overview on the accuracy of alternative VaR methods see Lu, Wu, and Ho (2009). Liow (2008) analyzes the VaR dynamics of international securitized real estate and stock market returns using extreme value theory (EVT) based on the block maxima method.

Having defined an adequate risk measure for the single REIT, we need to model the risk spillovers between REITs. Since spillovers are not constant over time but instead change over different states of the market and depend on the financial health of a firm a suitable model needs to incorporate these conditions. Our SDSVaR model (Adams, Füss, and Gropp, 2012), is related to Adrian and Brunnermeier's (2011) CoVaR approach. Both methods focus on modelling risk spillovers. However, our approach explicitly accounts for the response magnitude of REITs to shocks during changing conditions of financial health. The quantile regression framework that will allow us to do so was inspired by the CAViaR model of Engle and Manganelli (2004).

For our purpose we apply a slightly modified version of the state-dependent sensitivity value-at-risk (SDSVaR) framework. The SDSVaR follows the two-step process of computing a REIT's standard VaR in a first step, and estimating the risk spillovers between two REITs in a second step.

In the first step, we estimate the VaR for each REIT m :

$$\widehat{VaR}_m = \hat{\mu}_{m,t} + z\hat{\sigma}_{m,t}. \quad (1)$$

with $\hat{\mu}_{m,t}$ as the mean of REIT m at time t , $m = 1, 2, \dots, 74$, and z as the 5% quantile of the standard normal distribution. It has become practice to model $\hat{\sigma}_{m,t}$ by extracting the conditional standard deviation from a GARCH model (Kuester, Mittnik, and Paolella, 2006). This will account for the time-varying volatility of returns and leads to substantial improvements in the sensitivity of the VaR to changes in the return process.¹¹ The VaR is

¹¹ For most of our return series volatility responds more strongly to negative return changes than to positive ones. To capture this fact we apply the asymmetric Exponential GARCH(1,1) of Nelson (1991) with a conditional t -distribution for the error terms. Adams, Füss, and Gropp (2012) also computed the VaR series in Equation (1) using the asymmetric slope version of Engle and Manganelli's (2004) CAViaR model and obtain similar empirical results. Note further that technically the VaR is just a linear function of the volatility so that

then the estimated loss of a REIT that, within a given period (usually 1 to 10 days), will be exceeded with a certain probability θ (usually 1% or 5%):

$$\text{prob}[return_t < -VaR_t | \Omega_t] = \theta. \quad (2)$$

However, this conditional VaR measure only includes the own past return history, i.e. $\Omega_t(VaR) = \{r_{i,t-1}, r_{i,t-2}, \dots, r_{i0}\}$, and does not incorporate the additional risk in REIT i caused by REIT j being in distress. Hence, in our SDSVaR approach we expand the information set Ω_t by including also the VaR of another REIT j :

$$\Omega_t(SDSVaR) = \{r_{i,t-1}, r_{i,t-2}, \dots, r_{i0}, VaR_{j,t}\}. \quad (3)$$

In the second step, \widehat{VaR}_m now becomes the dependent variable and is modeled by its own lag, the VaR of the REIT from which the spillover originates, and some control variables Z . For instance, in terms of a shock to the VaR of some REIT j causing spillovers to another REIT i , the spillover equation is described by

$$\widehat{VaR}_{i,t,\theta} = \alpha_\theta + \beta_{1,\theta} \widehat{VaR}_{i,t-1} + \beta_{2,\theta} \widehat{VaR}_{j,t} + Z_t' \gamma_\theta + \varepsilon_t. \quad (4)$$

The vector of control variables Z includes the absolute price changes of the general U.S. REIT market, the VaR of the Russell 2000 small cap stock index, and an indicator of economic activity. Controlling for the absolute return changes of the general REIT market helps identifying the marginal spillover effect from REIT j and ensures that the coefficient estimate is not instead measuring some general movements in the REIT market.¹² In a similar way, the VaR of the Russell 2000 index captures the risk coming from the general stock

exactly the same spillover coefficients can be obtained using volatilities. However, we use VaR instead of volatility as the former has a more direct interpretation.

¹² The general REIT market is modeled by its absolute return changes instead of its VaR because of very high correlations between the VaR of the general REIT market and the VaR of most single REITs (correlations generally above 0.9). Other control variables that have been found to be insignificant and are thus not included are the 3-month Treasury bill rates, the REIT CDS index, and the VIX volatility index.

market.¹³ Stevenson (2002) examined the volatility spillovers on monthly REIT returns and found small cap and value stocks to be far more relevant for REIT returns than the general S&P 500 index or growth stocks.¹⁴ The purpose of the economic activity variable is to control for regional shocks that could cause two REITs with properties located in the same U.S. state to co-move. This variable is measured in monthly frequency for all states that accommodate the properties of the shock receiving REIT.¹⁵ Like the general REIT index and the small cap index, the economic activity indicator helps to separate the spillover effects from simple co-movements.

Equation (4) is estimated in a system of two equations with the second being the equation for $Var_{j,t,\theta}$. The method of estimation is two-stage quantile regression.¹⁶ Although Equation (4) could be easily estimated by OLS, the resulting spillover coefficient would be an estimate for the average risk spillover over the entire period from 06/01/2007 to 16/03/2011. With quantile regression, however, we are able to obtain spillover estimates for different quantiles of the dependent variable. Accordingly, we estimate the spillovers conditioning on the financial health of the REIT receiving the spillovers. We can observe how risk spillovers differ when the REIT that receives the spillover is in financial distress

¹³ Note the analogy to the systemic risk literature (e.g., Acharya et al., 2010; Brownlees and Engle, 2011) where it is emphasized that shocks from one financial institution to another cannot be measured in isolation. Instead, the relationship of the entire financial system has to be controlled for.

¹⁴ Replacing the Russell 2000 small cap index by the Russell 2000 value index leads to qualitatively identical and quantitatively similar empirical results. The same is true if we use the absolute returns of the Russell 2000 index instead of its VaR. The times series for the REITs and the stock market indices are taken from the SNL databank as well as Thomson Reuters Datastream. To conserve space, we do not show the results here, however, they are available from the authors upon request.

¹⁵ This means that economic activity will be only measured for a subset of all U.S. states, depending on the location of the properties of the REIT on the left-hand side of the equation. This approach improves estimation efficiency and helps to avoid linear dependencies. Economic activity is obtained from the FRED database at <http://research.stlouisfed.org>. For stationarity reasons, it is measured in percentage changes.

¹⁶ See Powell (1983) for the derivation of the statistical properties of this estimator.

(low quantiles of the VaR distribution), during normal times (median of the VaR distribution), or during tranquil periods (high quantile of the VaR distribution). We choose the 12.5% quantile for the financial distress state, the 50.0% quantile for the normal state, and the 75.0% quantile for the tranquil state.¹⁷ While the median is a natural choice for the normal state and the particular choice for the upper quantile usually has little effect on the results, the lower quantile is more controversial. The 12.5% is to some degree arbitrary but reflects the trade-off between estimates that are obtained from a few observations with very large weights versus being too far from the lower distribution tail. The quantile is indicated by the index θ in Equation (4).

A second issue is the possibility of feedback effects. A shock to the VaR of REIT j may spillover to REIT i , but does not need to be unidirectional. Instead there could be substantial feedback effects from REIT i back on REIT j . This raises the statistical problem of endogeneity that has to be dealt with.¹⁸ Two-stage quantile regression is suitable for capturing the simultaneity in the VaR spillovers and their quantification during different financial states of the REIT. We identify the system by assuming that the own lag $VaR_{i,t-1}$ only affects the VaR of institutions i . Hence, controlling for contemporaneous spillover effects from REIT j and the control variables Z , there is no additional spillover effect of the lagged VaR of the other REIT j . At the same time the coefficients for the own lagged VaR (e.g., $\beta_{1,\theta}$ in Equation (4)) are statistically significant and therefore constitute valid instruments to identify the system (Wooldridge, 1999).¹⁹ Adapting the methodology from two-stage least squares to

¹⁷ Thus, while the 5%-quantile of the return distribution is the VaR, low quantiles of the VaR distribution constitute the VaR during times of financial distress. The former is necessary to obtain the desired risk measure, but it is the latter that introduces state dependency into the model.

¹⁸ We make the assumption that single REITs are not large enough in order to have feedback effects on the general REIT index and on the small cap stock index.

¹⁹ Second lag instrument, $\widehat{VaR}_{i,t-2}$, is insignificant and including it has no effect on the results.

our quantile regression setting is rewarded with consistent estimates that account for the fact that the VaRs of interdependent REITs are determined simultaneously.²⁰

We estimate the risk spillovers for all combinations of the 74 REITs, i.e. $74 \times 73 = 5,402$ quantile regressions over three states or a total of 16,206 regressions. Table 1 shows the coefficient estimates of the SDSVaR model.²¹ We summarize the results in each state by showing the descriptive statistics of the four coefficients.²²

When the REIT receiving the risk spillover experiences calm market returns, the spillover is on average 0.023 (significant in 72.3% of all cases), i.e. a one percent increase in the VaR of REIT j increases the VaR of REIT i on average by 0.023%. Although this coefficient is significant in most of the regressions, the absolute value is relatively small. However, the same 1% increase in the VaR of REIT j leads to a 0.047% increase during normal times and a 0.128% increase on average if the shock receiving REIT is in financial distress.²³ Compared to normal times, the risk spillover is therefore more than twice the size when we consider the left tail of REIT i 's VaR distribution. Column 3 in Table 1 shows the

²⁰ Note that in two-stage quantile regression, like in TSLS, each equation is estimated separately. The state of the market is determined by the quantile of the left-hand side variable.

²¹ Note that the coefficient standard errors are not only determined by the sampling error in the quantile regression framework but also by the uncertainty within the VaRs themselves which depend on the GARCH coefficients. However, the large number of regressions make bootstrapping impractical so that the fraction of significant parameters in Table 1 is derived from common asymptotic standard errors. We view this drawback to be of minor relevance since the main results in this paper are based on the cross-section of spillover coefficient estimates rather than their standard errors (see section 4).

²² The intercept and the coefficients for economic activity are suppressed. Economic activity depends on the shock receiving REIT and cannot be easily summarized in one number. However, the majority of economic activity coefficients are insignificant and, more generally, economic activity does not alter the results in Table 1.

²³ The financial distress period is represented by the 12.5% quantile of the VaR distribution. The choice for this quantile is to some extent arbitrary. For instance, the spillover coefficient of 0.128 would increase to 0.142 if we had selected the 10% quantile, and it would decrease to 0.117 for the 15% quantile. However, the coefficient estimates do not change dramatically and the exact choice of a low quantile has no material impact on our main results.

coefficient for the $t-1$ lag of REIT i 's VaR. The VaR appears to be strongly autoregressive with a coefficient that is close but below unity.²⁴ The VaR of the Russell 2000 small cap index has a small but positive sign, indicating that an increase in risk of small cap stocks tends to increase the risk of REITs. This coefficient is significant in 20-30% of all cases. Finally, the last column shows the effect of the absolute return changes in the general REIT index. As expected, changes in returns indicate higher uncertainty in the overall REIT market which leads to a more negative (i.e., increasing) VaR of single REITs. Furthermore, the general REIT market appears to be more relevant in times of financial distress where it is significant in about 80% of all regressions.

<<< Table 1 about here >>>

4 Explaining Risk Spillovers: The Cross-Sectional Setting

In the previous section we have demonstrated that risk spillovers among single REITs exist and can be substantial, depending on the financial health of the REIT. The purpose of this section is to identify the determinants of those risk spillovers. While in the previous section, risk spillovers were obtained from daily time series of VaR measures, our aim in this section is to explain the risk spillovers over the cross-section of REITs. Specifically, we are interested in the risk gradient which shows the risk spillover size as a function of geographical distance. We expect risk spillovers to be larger when two REITs have their properties located in the same region. In this case, property values will be affected by the same local economic conditions such as local employment characteristics or land supply restrictions. With increasing distance, we expect risk spillovers to decrease but to stabilize at a positive value. This value reflects linkages in the property market through national

²⁴ The autoregressive structure in the VaR is a result from the well-known serial correlation in daily financial volatility that is captured by the conditional GARCH standard deviation $\sigma_{m,t}$ in Equation (1).

economic variables but also linkages in the financial market through normal asset similarities. Finally, we are able to explain the variation in risk spillovers through a selection of financial variables that have been found to be relevant in the systemic risk literature (Acharya et al., 2011; Adrian and Brunnermeier, 2011). These factors complement our analysis on the impact of balance sheet variables on risk spillovers of REITs.

4.1 Data

We acquire the dependent variable as the risk spillovers estimates from section 3.²⁵ The property holdings for individual REITs are obtained from the SNL databank at the reference date 2011Q1. REITs are subject to certain property-selling restrictions that are required in order to maintain their tax-exempt status. For instance, REITs must hold acquired properties for a minimum period of four years. Furthermore, they are not allowed to sell more than 10% of their net asset base within a given tax year (see, e.g., Mühlhofer, 2011). Empirical studies on the actual holding periods of commercial property in the U.S. find an average holding period of 11 years (Fisher and Young, 2000). In a study for the U.K. market, Collett, Lizieri, and Ward (2003) find that this average is higher during market downturns when returns are lowest and disposition of a property would result in a loss for the investor. This effect is further amplified by restricted access to financing, lower liquidity, and hence higher transaction costs increasing holding periods even further. This provides support for a necessary assumption in the empirical section of our paper: we assume property holdings to remain constant during our period of investigation (2007 – 2010) which includes the 2008-09 financial crisis period. The following five regressors are obtained from the balance sheets of

²⁵ Compared to the SDSVaR estimation, the use of estimated as opposed to actually observed spillovers in the cross-sectional setting does not cause an estimation problem because the estimated price series assumes the role of the dependent variable in our cross-section model rather than that of an independent variable. That means we are adding a measurement-in-error problem to the left side of the second stage regression rather than to the right side. As is well-known, dependent variables measured with error do not cause a fundamental estimation issue because the measurement error is captured in the ordinary regression error term.

the REITs (from the SNL datrabank) and are measured as average annual values between 2007 and 2010, the time period over which the risk spillovers were estimated (time period 06/01/2007 to 16/03/2011). The sixth regressor is estimated from monthly market data over the same period. The selected REITs in our sample are mainly domestically invested, only a few properties are located in Canada or Mexico. However, given the large number of included properties, their impact is negligible.

1. *Property type*: In a recent study, Chiang (2010) shows that price co-movements among REITs within the same property type have increased over time. If the prices of some property types are more sensitive to changes in economic conditions than others risk spillovers among specialized REITs are likely to differ as well.²⁶ Chiang argues that the information openness due to high institutional participation, low insider ownership, and large market capitalization supports the price discovery process of property-type information and the pricing on firm level. Capozza and Seguin (1999) show that REITs with a strong sector focus are less complex in monitoring and more transparent than REITs holding diversified portfolios. Hence, we also control for the company size of REITs.
2. *Size*: Large REITs tend to be represented with properties in many regions across the country and may be therefore more sensitive to national economic conditions. Moreover, in line with the arguments of Chiang (2010), prices of large-capitalized REITs may contain a higher degree of systematic information. Size is approximated by total enterprise value, i.e. company's debt plus equity.

²⁶ If at least 90% of a REIT's properties are of the same property type we classify this REIT as the corresponding type. Most REITs are classified as being either retail (25), office (24), or residential (19) REITs. Only six REITs were classified as industrial. A complete list of the REITs used in the empirical part is given in Table A1 in the Appendix.

3. *Leverage*: Although REITs rely heavily on leverage to finance commercial properties we expect the importance of leverage for risk spillovers among REITs to be much lower than for financial institutions.²⁷ Financial institutions use leverage to hold each others assets in their portfolio so that in the presence of a shock, spillovers occur when financial institutions sell other institutions stocks. Still, REITs with higher leverage are associated with higher risk and are therefore more likely to react stronger to risk spillovers (see Cici, Corgel, and Gibson, 2011). Leverage is computed as total assets divided by total book equity.
4. *Maturity mismatch*: Companies that have the majority of their debt denominated as short-term debt are generally in greater need of cash and hence more sensitive to losses and market distress. This should be particularly prevalent in market periods where investors prefer liquidity and refinancing conditions tighten. We expect companies with a large maturity mismatch to be more sensitive to risk spillovers. Maturity mismatch is defined as [short-term debt plus debt due this financial year minus cash] divided by total liabilities.
5. *Market-to-book*: Past empirical evidence has shown that some investors tend to overinvest in stocks that have done very well in the past contributing to an overpricing of such stocks (Lakonishock et al., 1994, Griffin and Lemmon, 2002). Similarly, it has been observed that investors tend to overreact to stocks that have performed very poorly pushing their prices below their fundamental value. Since investors eventually realize that the past performance of many REIT stocks does not prevail in the future we expect stocks with high market-to-book values to be more sensitive to risk spillovers.

²⁷ The median leverage of the REITs in our sample is approximately three, i.e. two-thirds of the capital is debt. Prior to the early 2000's when REITs started to increase their leverage, REITs typically had no more than a one-to-one debt-to-equity ratio (see also Gyourko, 2009).

6. *Market beta*: Taking the S&P 500 composite index as the market return we use the beta of a REIT as an indication of its general stock market linkage. The stock market linkage is likely to be an important source of risk spillovers for REITs that have no direct spatial dependence. We expect firms that have high betas and thus a stronger dependence on stock market movements to be more exposed to risk spillovers.

An overview of these financial variables is given in Figure 4. Maturity mismatch is given in percent of total liabilities and size is measured in millions of U.S. dollars. Compared to financial institutions, leverage is relatively low among REITs. In addition, only a small fraction of total liabilities is in the form of short-term debt which is reasonable given their long investment horizon. One potentially important variable not included in our model is REIT liquidity. Liquidity becomes relevant when a price drop in REIT j induces investors to sell the stocks of REIT i . If REIT i 's stocks are illiquid the price impact from trading REIT i and hence the spillover from j to i will be larger. However, liquidity is typically strongly time-varying. A measure of average liquidity in a cross-sectional setting spanning a four year period would be uninformative. What is relevant for explaining the variation in spillovers is not the average liquidity but the amount of liquidity at the moment when the spillover occurs.²⁸

²⁸ Marshall, Nguyen, and Visaltanachoti (2012) furthermore show that more generally, low frequency measures are not suitable for capturing the underlying liquidity of an asset. We also estimated a version of Equation (4) that includes illiquidity in an interaction term with the VaR of REIT j . In contrast to the cross-sectional setting that required to take the time mean over a REIT's liquidity, Equation (4) estimates the spillovers in a time-series that allows for the inclusion of the daily variation in liquidity. Our results (not shown) were however inconclusive. Although the spillover coefficients are very close to the ones reported in Table 1, our Amihud illiquidity measure (daily absolute returns divided by volume) was only significant in 50%, 29%, and 14% of all times for volatile, normal, and tranquil periods, respectively. A further disadvantage of this approach is that the marginal spillover effects become hard to interpret as the interpretation relies on a given level of liquidity. Because of the high variability in liquidity, the usual approach of inserting the average liquidity could not be applied.

In estimating the model we treat the financial variables as categorical instead of continuous variables. Recall that the cross-section consists of 5,402 observations obtained from regressing all combinations between two of the 74 REITs. Accordingly, among the 5,402 observations in the sample only 74 values of each variable are unique and each value is repeated 73 times. In addition, the values are distributed very unevenly over the range of the variables with clusters for low, middle, and high values. This clustering of values is demonstrated in the lower panel of Figure 4 for the variable leverage.²⁹ We therefore split each variable in three categories. The first decile represents low values of that category, and the last decile representing the upper end of the variables. Grouping the variables in this way allows for a clear distinction between the values. Note, for instance, that the first and third quartile as shown in Panel A for leverage are quite close together. Our results still hold for more moderate classifications but are less clear and become mixed for cut-off points that are closer to the median such as 0.3 and 0.7, respectively.

<<< Figure 4 about here >>>

Finally, we construct a measure of geographical distance between any combination of two REITs. This task is complicated by the fact that a meaningful measure has to be based on the geographic location of the properties that are owned by the REITs. We obtain information on the latitude and longitude of all 16,418 properties which are distributed over the 74 REITs. Distance D is computed using the Haversine formula which gives the shortest distance over the earth's surface³⁰:

²⁹ The distributions for the other variables look very similar. The only variable that does not indicate strong clustering is market beta. In order to be consistent we also transformed this variable into categorical form but the empirical results are similar when beta enters the model as a continuous variable.

³⁰ In an earlier version of this paper we also tried adjusting the distance for the size of the properties and the percentage owned. Assuming the nearby presence of two large properties to be more relevant for risk spillovers than two small properties, we considered both factors as contributing to a measure of "economic importance" rather than just geographical distance. However, we decided against this approach as it dilutes the

$$D = R \cdot c \tag{5}$$

where R is the earth's radius (3,959 miles), $c = 2 \cdot \text{atan}_2(\sqrt{a}, \sqrt{1-a})$, $a = \sin^2(0.5 \cdot \Delta \text{lat}) + \cos(\text{lat}_1) \cdot \cos(\text{lat}_2) \cdot \sin^2(0.5 \cdot \Delta \text{long})$, and lat and long are the latitude and longitude of a property measured in radians.

To determine the distance between two REITs, say REIT i and REIT j , we successively compute the distance of each property in REIT i to all other properties owned by REIT j in order to identify the property of REIT j with the shortest distance to the properties of REIT i . This approach follows the intuition that we are particularly interested in the presence of nearby properties which are affected by the same local economic conditions.³¹ Having detected the nearest properties of REIT j for all properties of REIT i , we take the average over all distances of those properties to find the geographic distance between REIT i and REIT j . To illustrate this mechanism Figure 5 shows the geographical distribution of the properties of two REIT pairs together with their calculated distance. The left graph shows two REITs with properties in very similar locations. The distance between the REITs is estimated to be 9.08 miles, the closest distance in our sample.³² The right graph shows two REITs with very long distances between their properties. For this particular example, the

spatial aspect and prevents an intuitive interpretation of the risk gradient. Moreover, because distance and economic variables are no longer independent, the additivity property of the estimates for the determinants of the spillover coefficients in the nonparametric (nonlinear) and the parametric (linear) part of Figure 6 in subsection 4.2 would no longer hold.

³¹ As a consequence of this approach the distances between two REITs are not symmetric, i.e. the distance from REIT i to REIT j is not the same as the distance from REIT j to REIT i . We make the distance matrix symmetric by taking the averages between both REIT's distances.

³² This distance is still a multiple of the space that is investigated in the foreclosure literature (Lin, Rosenblatt, and Yao, 2009; Harding, Rosenblatt, and Yao, 2009) where the transmission mechanism of spillovers is largely visual.

spillover estimates between the REITs with the small distance is roughly 11 times larger than the spillovers between the large distance REITs.

<<< Figure 5 about here >>>

4.2 Empirical Results

Among our variables to explain risk spillover size we are particularly interested in the risk gradient, the function describing the relationship between spillovers and geographical distance. To allow a maximum amount of flexibility we therefore model the effect of geographical distance non-parametrically while the effects of the balance sheet regressors are modelled in the usual parametric way.³³ Thereby, the fact that geographical distance is unrelated to any of the financial variables in the model allows us to estimate the nonparametric part and the parametric part separately.³⁴ Panel A of Figure 6 shows the scatter plot of risk spillovers as a function of distance together with the predicted nonparametric estimate for tranquil, normal, and volatile REIT states. As expected, REITs that are in a state of financial distress experience much higher risk spillovers than during normal or tranquil periods. In addition, risk spillovers are higher among REITs that have their properties located in adjacent regions. For instance, REITs within a 60 miles distance radius have on average 33% higher risk spillovers than otherwise identical REITs with distances of more than 250 miles. For the REITs with the shortest distance (about 9 miles), risk spillovers are estimated to be roughly 0.18, i.e. a one percent increase in the value-at-risk of one REIT increases the VaR of another REIT on average by 0.18%. This risk spillover then decreases nonlinearly and spillovers remain basically unchanged for distances of more than 250 miles. The distance

³³ For the nonparametric part we use the second order local polynomial regression.

³⁴ If we include distance in the parametric model the coefficients of distance and squared distance are highly significant but the parameters of all other regressors change only marginally which confirms the validity of our approach.

of 250 miles therefore seems to mark the border at which the influence of local economic effects ends and only national economic effects and general stock market linkages remain. The empirical finding supports Dolde and Tirtiroglu (1997, 2002) who report that regional proximity plays an important role for transmitting volatility among housing markets, and is closely related to Zhu, Füss, and Rottke (2011), who find substantial co-movements among regions with a distance of less than 250 miles but no evidence for co-movements for distances of more than 750 miles.³⁵ Since a nonparametric function yields no coefficient estimates we show the percentage marginal effects at selected points of the function in the right graph of Panel A. For instance, increasing the distance from 10 miles to 11 miles is estimated to reduce the risk spillover by 0.36%. One additional mile at a distance of 100 miles reduces the risk spillover by only 0.27% while at 250 miles the slope is flat with no effect of an increase in distance.

<<< Figure 6 about here >>>

Panel B of Figure 6 shows the coefficient estimates of the linear parametric part which explains risk spillovers by property type and the financial variables obtained from the balance sheets of REITs. As before, we distinguish between the three financial conditions. In these models, property type and the other financial variables enter the regression in categorical form. For instance, the parameter estimate for the property type indicates that, during times of financial distress, risk spillovers between two industrial REITs are on average 0.0356 higher than between two REITs with unequal property type. Similarly, compared to REITs with low levels of leverage, medium or highly leveraged REITs are estimated to have risk spillovers that are about 0.0414 to 0.0588 higher which constitutes a large increase in risk sensitivity.³⁶

³⁵ The similarities with the results in Zhu, Füss, and Rottke (2011) are noteworthy since the authors reach this conclusion using a very different methodology.

³⁶ Perhaps unexpected, the coefficient for high leverage is lower than of the categorical variable medium leverage. This result can be partly explained by the fact that the majority of REITs in our sample underwent a

Two other variables that are estimated to have impacts of similar magnitude are firm size with spillover estimates of 0.0555 for the 10% largest companies during a volatile market phase, and firms with a high exposure to stock market changes as measured by beta (0.0613 during volatile financial conditions). To a lesser extent, we can also expect larger spillovers from REITs with higher maturity mismatch or market-to-book values. Finally, we control for relevant characteristics on the side of the REIT transmitting the risk by adding fixed effects for this REIT. The REIT fixed effects are an elegant way to control for all relevant variables without having to model them explicitly and they contribute to overall explanatory power.³⁷ Property type, the balance sheet regressors, and REIT transmitter fixed effects explain about half of the total variation in risk spillovers. As an example, consider a REIT A during a volatile phase (0.0795) that mainly holds industrial properties (0.0356), has medium leverage (0.0588), large size (0.0555), high maturity mismatch (0.0231), has a high beta (0.0613), and has its properties located within a 9 miles distance radius (0.18-0.117) to another REIT B. In

process of substantial deleveraging. For instance, of the 10 REITs that were allocated to the highest 90% leverage group in 2007, only two were left in 2010 while the other 8 moved to the medium leverage group. On average, deleveraging REITs reduced their leverage by 22%. We estimated a version of Figure 6 that includes the amount of deleveraging in percent and an interaction term of deleveraging with leverage itself (not shown but available upon request). In this modified regression, the coefficient for high leverage is higher than the coefficient for medium leverage, as expected. Another finding is that deleveraging tends to increase spillovers. One explanation for this finding would be that REITs were under pressure to reduce the high levels of leverage that emerged from the financial crisis. Strong deleveraging thereby might indicate that the levels were pushed well above their target leverage, leaving the REIT more vulnerable to adverse shocks.

³⁷ In estimations that explicitly include the balance sheet variables for the risk transmitting REIT we find similar variables to be relevant for risk spillovers, notably size. The *R*-squared in this setting is however lower indicating that other variables are important as well. Also note that the data is not a panel so that we cannot add both, balance sheet variables of the transmitting REITs and fixed effects.

this example, a 1% increase of the VaR of REIT B is estimated to increase the VaR of REIT A by 0.377% on average.³⁸

4.3 The Effect of Distance on the Dynamics and Persistence of Risk Spillovers

The risk spillover estimates from the preceding section marked the responses of REITs within the same day. However, if REITs are in fact interdependent and shocks are persistent it would seem reasonable to expect reactions to the initial shock to last over a longer time period. In this section, we address this issue by presenting impulse response functions that show the dynamic behavior of a system of two REITs in the presence of a one-time shock to one of the REITs. As an example we consider the two companies Essex Property Trust (ESS), a residential REIT, and Kilroy Realty Corporation (KRC), an office REIT. These REITs have their properties located in the same regions and their estimated distance is only about 9 miles. The estimated coefficients for KRC according to Equation (4) are

$$\begin{aligned}\widehat{VaR}_{KRC,t} &= 0.001 + 0.751 \cdot \widehat{VaR}_{KRC,t-1} + 0.366 \cdot \widehat{VaR}_{ESS,t} && (volatile) \\ \widehat{VaR}_{KRC,t} &= 0.000 + 0.851 \cdot \widehat{VaR}_{KRC,t-1} + 0.157 \cdot \widehat{VaR}_{ESS,t} && (normal) \\ \widehat{VaR}_{KRC,t} &= 0.000 + 0.882 \cdot \widehat{VaR}_{KRC,t-1} + 0.091 \cdot \widehat{VaR}_{ESS,t} && (tranquil)\end{aligned} \quad (6a)$$

For simplicity, the equations in (6a) do not report the coefficients on the control variables of Equation (4) which are exogenous and can be ignored for the estimation of the impulse response functions. As expected, the risk spillovers are high during volatile times and become smaller for more tranquil periods. The corresponding equations for ESS are

$$\begin{aligned}\widehat{VaR}_{ESS,t} &= 0.002 + 0.769 \cdot \widehat{VaR}_{ESS,t-1} + 0.229 \cdot \widehat{VaR}_{KRC,t} && (volatile) \\ \widehat{VaR}_{ESS,t} &= -0.001 + 0.850 \cdot \widehat{VaR}_{ESS,t-1} + 0.120 \cdot \widehat{VaR}_{KRC,t} && (normal) \\ \widehat{VaR}_{ESS,t} &= 0.000 + 0.878 \cdot \widehat{VaR}_{ESS,t-1} + 0.077 \cdot \widehat{VaR}_{KRC,t} && (tranquil)\end{aligned} \quad (6b)$$

³⁸ Note that the impact of distance from the nonparametric part equals 0.1800 minus 0.117 with the latter being the co-movement size at 250 miles distance which is determined by national economic impacts and stock market linkages.

In contrast to correlation coefficients which are symmetric by construction, the spillover coefficients are directional and asymmetric. In particular, a shock in ESS is estimated to provoke a larger response in KRC than an identical shock going in the other direction.

The lower left graph in Figure 7 shows the response of Kilroy to a one time shock from Essex for each financial state. Because of the generally high persistence in the volatility and thus in the SDSVaRs, responses accumulate and peak at about 15 trading days after the shock. If the shock receiving REIT (KRC) is in a normal or volatile financial condition, the responses are large and stay in the system for several months.

We contrast these strong risk linkages with a hypothetical situation, in which the distance between the two REITs is increased to 500 miles but all other characteristics are held constant. This approach highlights the impact of geographical proximity not only on the immediate response size but also on the short-term dynamics in the system. We use the nonparametric regression approach from the previous section which predicts that spillover coefficients in Equation (6a) would decrease to 0.25, 0.10, and 0.05 for volatile, normal, and tranquil states, respectively. Similarly, we replace the spillover coefficients in Equation (6b) by their lower estimates of 0.16, 0.07, and 0.05. The other coefficients are assumed to remain unchanged. The lower right graph in Figure 7 shows the responses for this counterfactual situation. The two REITs are now no longer linked by local economic conditions but only through broader national economic changes and stock market changes. The response to changes in risk and the persistence to those changes are therefore significantly lower. After Essex experiences a one-time shock, the responses die out quickly and vanish entirely after about 40 days.

The empirical results from this example highlight how regional proximity, in which spillover size is only about 58% higher than in the counterfactual long-distance case has substantial impact on both, spillover size and persistence.

<<< Figure 7 about here >>>

5 Conclusion

In this paper, we investigate the impact of geographical proximity on the risk spillovers of REITs. We obtain a distance measure by comparing the latitude and longitude information of the properties owned by the REITs. The risk gradient, a measure of spillover size as a function of geographical distance indicates large spillovers for REITs that have their properties in close distance. This function decreases nonlinearly and is flat for distances of more than 250 miles. Within a radius of 50 miles, local economic linkages cause risk spillovers to be on average 43% higher than spillovers among REITs that are more than 250 miles apart. We interpret this 250 miles range as the reach of local economic influence. Among the firm characteristics that can explain the cross-sectional variation in risk spillovers we find leverage, market beta, and company size to be the main drivers of spillover size.

A growing literature in the area of contagion and systemic risk indicates that spillovers are particularly relevant for the tails of a risk distribution, i.e. when one or more firms are in a state of financial distress. We demonstrate that risk spillovers depend on the financial conditions of the REIT responding to the spillover. While small during tranquil periods, risk spillovers can be substantial when the responding REIT is in financial distress. Our empirical findings highlight the relevance of geographical diversification and have important implications for the investment and risk management decisions of real estate investors, mortgage lenders, home suppliers, and policy makers.

Moreover, the laboratory of REITs with its straightforward business operations in a highly regulated sector provide us with the first empirical evidence how similarities in fundamental values transmit to the securitized level and trigger substantial risk spillovers. Our approach thus highlight the importance of accurate risk measurement within specific sectors such as financial institutions and industry companies, or portfolios such as mutual funds or loan portfolios.

Table A1: List of REITs by Property Type

Industrial (6)	Office (24)	Residential (19)	Retail (25)
AMB Property Corporation	Alexandria RE Equities, Inc.	Agree Realty Corporation	Acadia Realty Trust
DCT Industrial Trust Inc.	BioMed Realty Trust, Inc.	American Campus Commun.	CBL & Associates Prop.
Duke Realty Corporation	Brandywine Realty Trust	Apartment I. and M. Comp.	Cedar Shopping Centers, Inc.
EastGroup Properties, Inc.	Brookfield Office Properties	Associated Estates Realty.	Developers Div. Realty
First Industrial Realty Trust, Inc.	CapLease, Inc.	AvalonBay Communities	Equity One, Inc.
Monmouth Real Estate Invest Corp	Cogdell Spencer Inc.	BRE Properties, Inc.	Extra Space Storage Inc.
	CommonWealth REIT	Camden Property Trust	Federal Realty Inv. Trust
	Corporate Office Properties Trust	Colonial Properties Trust	First Potomac Realty Trust
	Douglas Emmett, Inc.	Education Realty Trust, Inc.	Glimcher Realty Trust
	Franklin Street Properties	Equity LifeStyle Properties	Inland Real Estate
	Gladstone Commercial	Equity Residential	Kimco Realty Corporation
	Highwoods Properties, Inc.	Essex Property Trust, Inc.	Macerich Company
	Kilroy Realty Corporation	Forest City Enterprises, Inc.	Pennsylvania RE Inv. Trust
	Lexington Realty Trust	Home Properties, Inc.	Public Storage
	Liberty Property Trust	Mid-America Apartment	Ramco-GershensonProperty
	Mack-Cali Realty Corporation	One Liberty Properties, Inc.	Regency Centers
	Mission West Properties, Inc.	Sun Communities, Inc.	Roberts Realty Investors
	Pacific Office Properties Trust	UDR, Inc.	Saul Centers, Inc.
	Parkway Properties, Inc.	UMH Properties, Inc.	Simon Property Group, Inc.
	PS Business Parks, Inc.		Sovran Self Storage, Inc.
	SL Green Realty Corp.		Tanger Factory Outlet
	Thomas Properties Group, Inc.		Taubman Centers, Inc.
	W. P. Carey & Co. LLC		Urstadt Biddle Properties
	Washington RE Investment Trust		U-Store-It Trust
			Vornado Realty Trust

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Table 1: SDSVaR Coefficient Estimates for Different States of Distress (06/2007–03/2011)

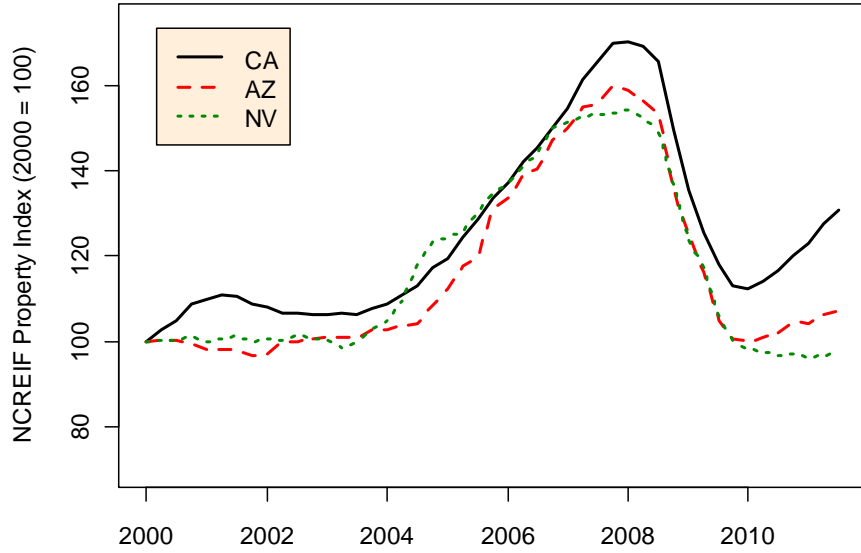
Tranquil				
	Spillover	Lag	VaR Russell	Ret. REIT Ind.
First Quartile	0.0052	0.9064	-0.0019	-0.0039
Mean	0.0232	0.9188	0.0036	-0.0015
Third Quartile	0.0346	0.9397	0.0095	0.0014
Standard Deviation	0.0251	0.0315	0.0092	0.0046
Skewness	1.5459	-2.0563	-0.3160	-0.8838
Excess Kurtosis	2.9081	6.3569	1.1803	2.9147
% Significant	72.29	100	21.83	26.43
Normal				
	Spillover	Lag	VaR Russell	Ret. REIT Ind.
First Quartile	0.0149	0.9018	-0.0033	-0.0081
Mean	0.0474	0.9221	0.0065	-0.0044
Third Quartile	0.0710	0.9509	0.0163	-0.0008
Standard Deviation	0.0455	0.0380	0.0158	0.0069
Skewness	1.0735	-1.2358	-0.1159	0.2012
Excess Kurtosis	1.2886	1.6168	2.3052	1.3672
% Significant	86.6	100	29.8	40.5
Volatile				
	Spillover	Lag	VaR Russell	Ret. REIT Ind.
First Quartile	0.0539	0.8836	-0.0258	-0.0491
Mean	0.1282	0.9325	0.0037	-0.0363
Third Quartile	0.1893	0.9924	0.0287	-0.0197
Standard Deviation	0.0948	0.0801	0.0504	0.0260
Skewness	0.7421	-0.7472	-0.0610	-1.0860
Excess Kurtosis	0.1696	0.3403	5.2277	3.1916
% Significant	87.8	100	24.9	77.9

This table shows descriptive statistics for 16,206 quantile regression estimates over the time period 06/01/2007 through 03/16/2011 (956 Obs.). We distinguish between three states of financial health (tranquil, normal, and volatile). Market states are measured by the 75%-, 50%-, and the 12.5%-quantile of the value-at-risk distribution of the responding REIT, respectively. The value-at-risk of REIT i is regressed on its own lagged value (Lag) and the VaR of REIT j (Spillover) controlling for the absolute returns of the S&P (General) U.S. REIT Index (Ret. REIT Ind.) and the VaR of the Russell 2000 Small Cap Index (VaR Russell):

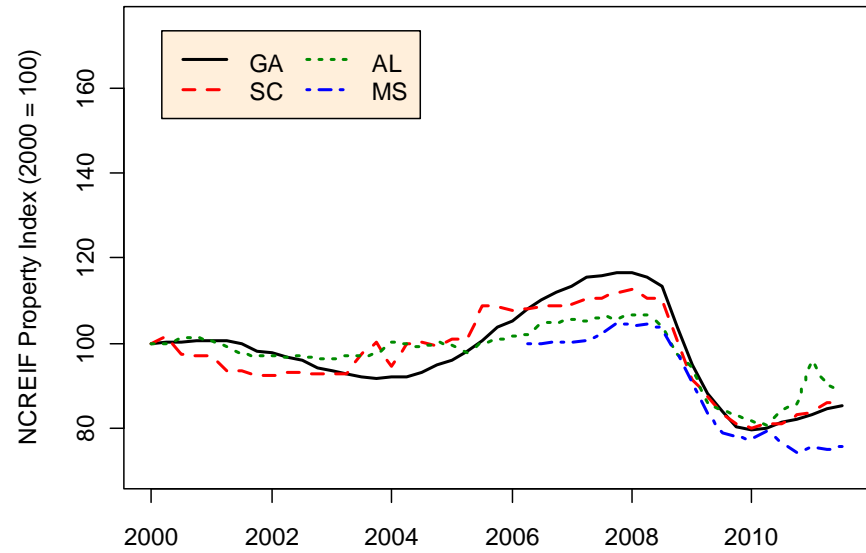
$$\widehat{VaR}_{i,t,\theta} = \alpha_{\theta} + \beta_{1,\theta} \widehat{VaR}_{i,t-1} + \beta_{2,\theta} \widehat{VaR}_{j,t} + \beta_{3,\theta} \widehat{VaR}_{Small.Cap,t} + \beta_{4,\theta} |Ret|_{REIT.Index,t} + \varepsilon_t$$

Figure 1: Regional Clusters in the NCREIF Property Index (NPI), 2000Q1–2011Q3

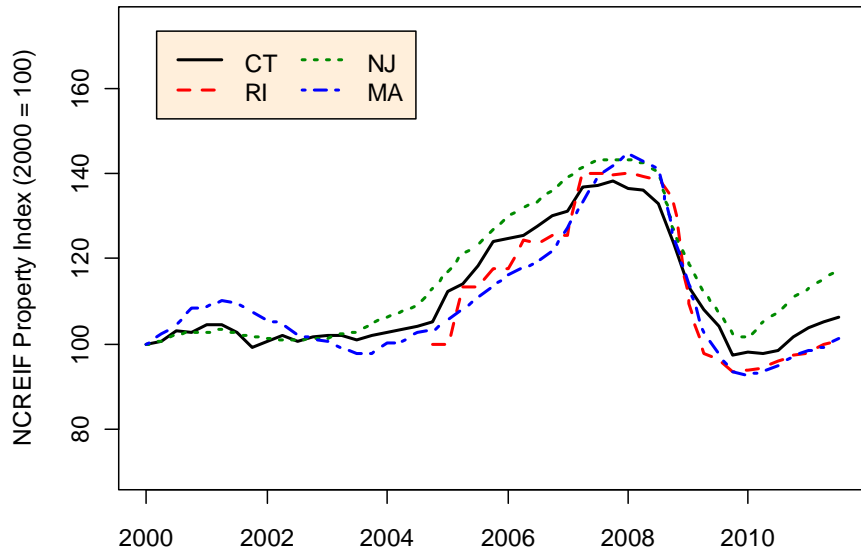
West Coast



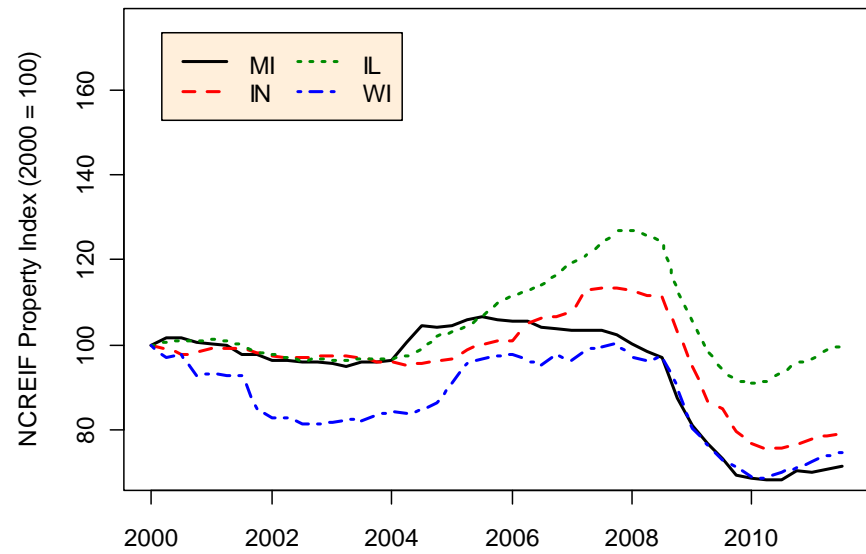
South East



North East



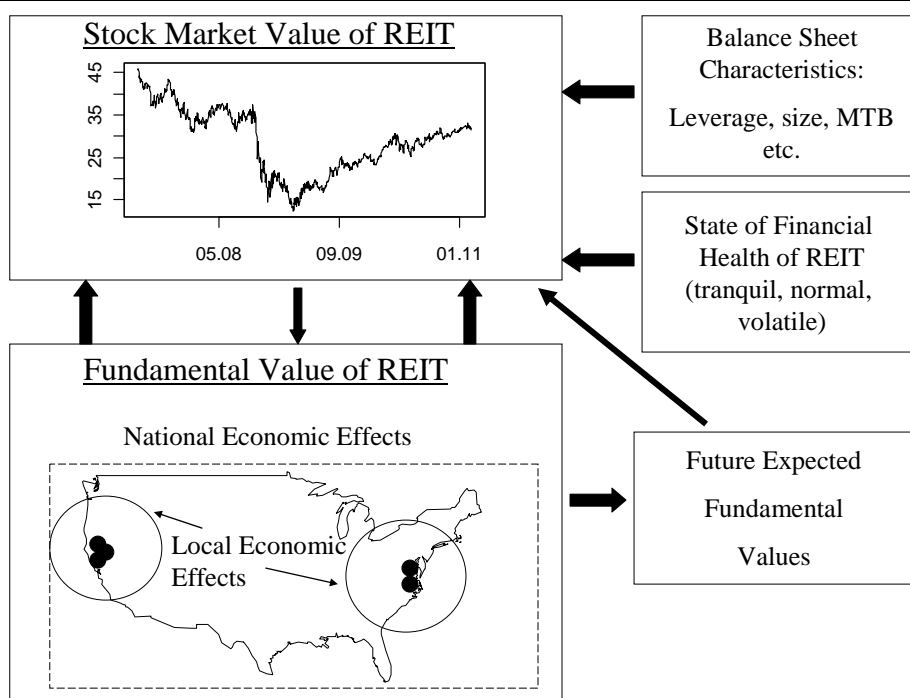
Midwest



This figure shows the property appreciation indices of NCREIF (NPI) for selected U.S. states on a quarterly basis from 2000Q1 to 2011Q3 normalized to 100 in 2000Q1. The NPI consists of a large pool of commercial real estate properties that have been acquired on behalf of tax-exempt institutional investors. The West Coast consists of Arizona (AZ), California (CA), and Nevada (NV); the South East includes Alabama (AL), Georgia (GA), Mississippi (MS), and South Carolina (SC); the North East includes Connecticut (CT), Massachusetts (MA), New Jersey (NJ), and Rhode Island (RI); the Midwest covers the states Illinois (IL), Indiana (IN), Michigan (MI), and Wisconsin (WI).

Figure 2: Risk Sources and Transmission Channels

Panel A: Sources of Risk Spillovers



Panel B: The Role of Distance for Risk Spillovers

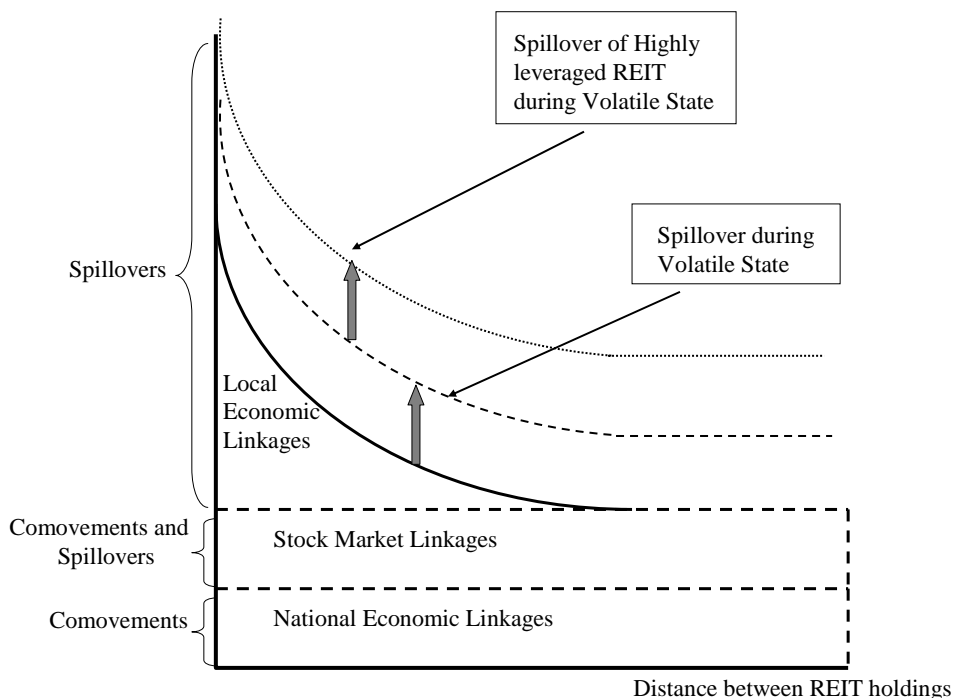
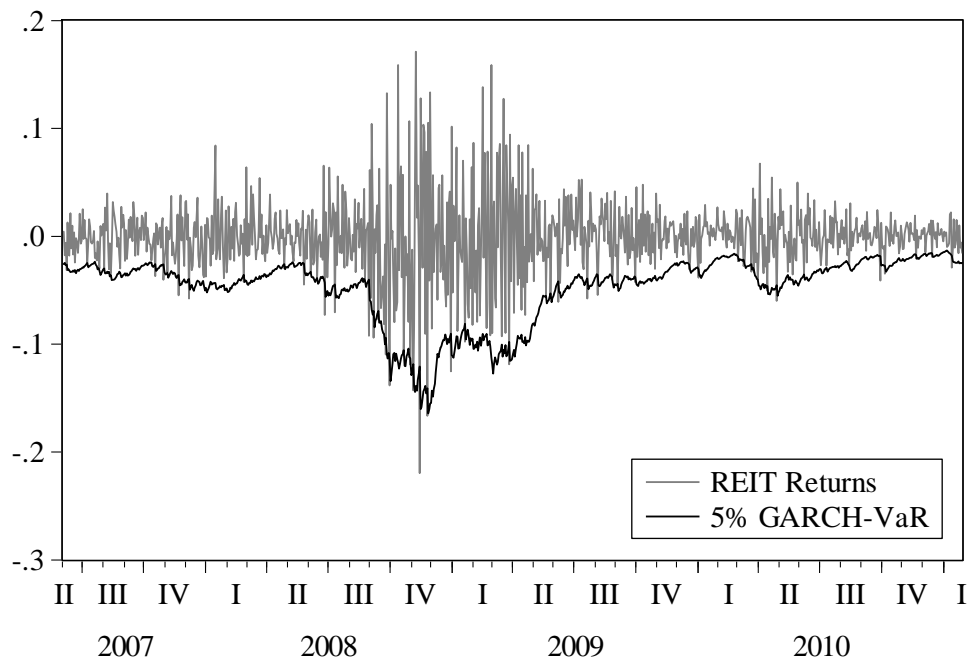


Figure 3: Daily Value-at-Risk of the U.S. REIT Market



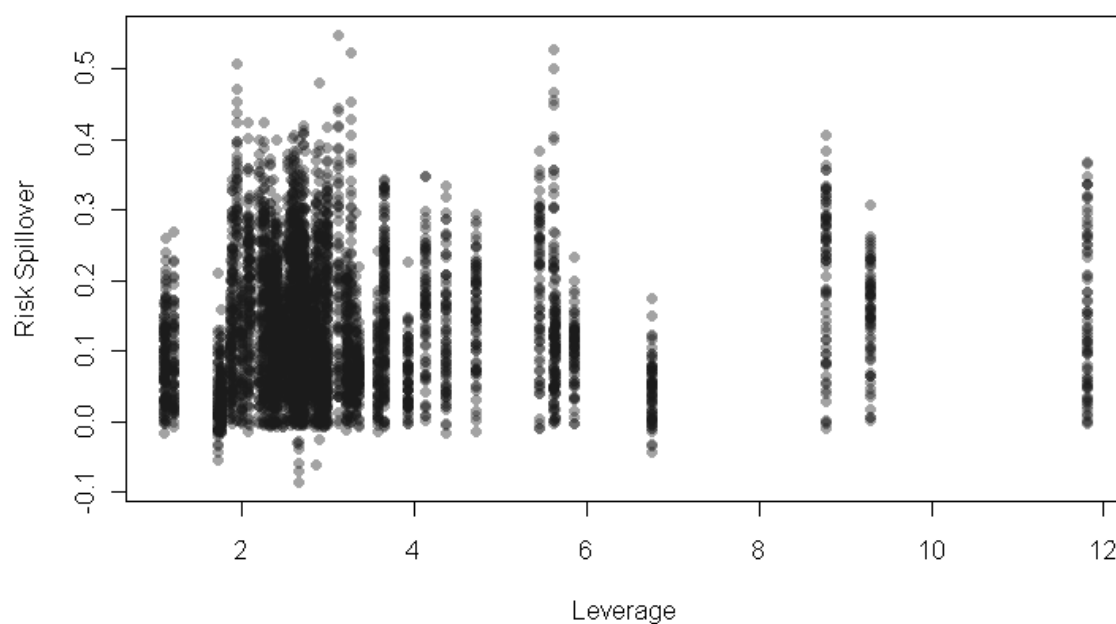
This figure shows the VaR of the S&P U.S. (General) REIT Index over the time period 06/01/2007 to 03/16/2011 including 956 return observations. The 5%-GARCH-VaR is based on asymmetric Exponential GARCH(1,1) process with a conditional t -distribution for the error terms.

Figure 4: Descriptive Statistics and Distribution of Regressors

Panel A: Descriptive Statistics for Selected Regressors

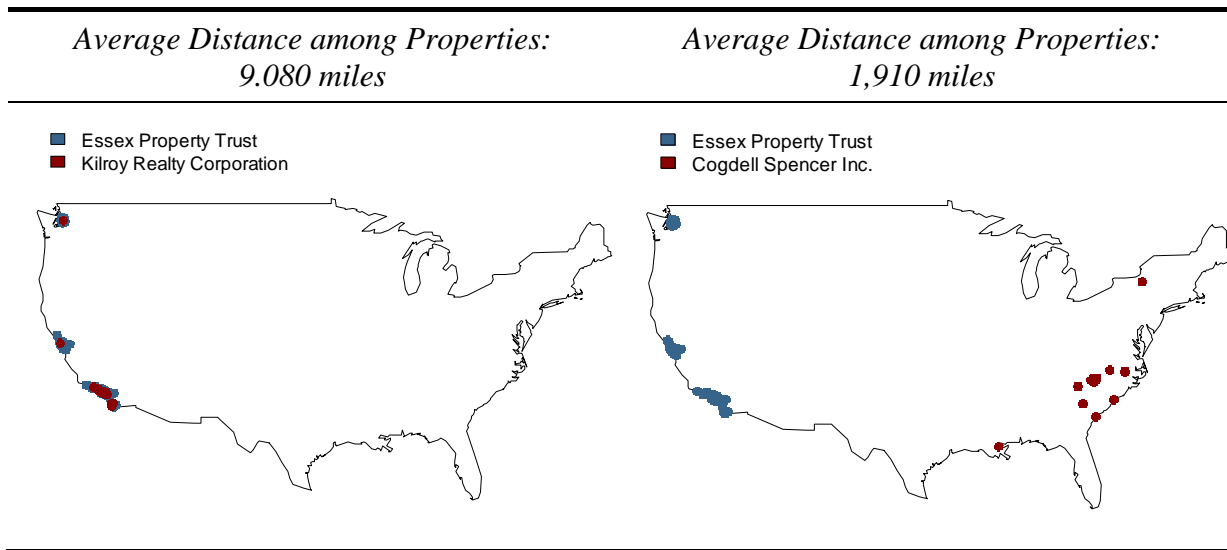
	Q.25	Median	Q.75	Std. Dev.	Skewness	Kurtosis
Leverage	2.36	2.71	3.25	1.80	2.63	8.03
Maturity Mismatch [%]	3.86	6.56	11.03	6.75	1.57	2.35
Market-to-Book	0.90	1.44	1.87	1.11	2.75	10.70
Size x 10⁶	1,497	2,857	6,123	6,398	3.50	15.69
Market Beta	0.62	0.83	0.95	0.38	0.37	0.63

Panel B: Distribution of Regressor Values: Leverage



Panel A shows the descriptive statistics of the balance sheet variables used as regressors to explain the size of risk spillovers. Leverage is computed as total assets divided by total book equity, maturity mismatch is given in percent and defined as (short-term debt plus debt due this financial year minus cash) divided by total liabilities and size is approximated by total enterprise value (company's debt plus equity) and is given in billions of U.S. dollars; market-to-book is defined as REIT's market capitalization divided by its total book value and market beta is the REIT's market sensitivity to S&P 500 Composite Index. Panel B shows the distribution of the leverage within our sample which highlights the need to treat the financial variables as categorical instead of continuous variables. Regressing each of the 74 REITs on the other 73 REITs leads to the observed scattering along a line of repeated leverage values.

Figure 5: Location of Properties and Estimated Distance between REITs

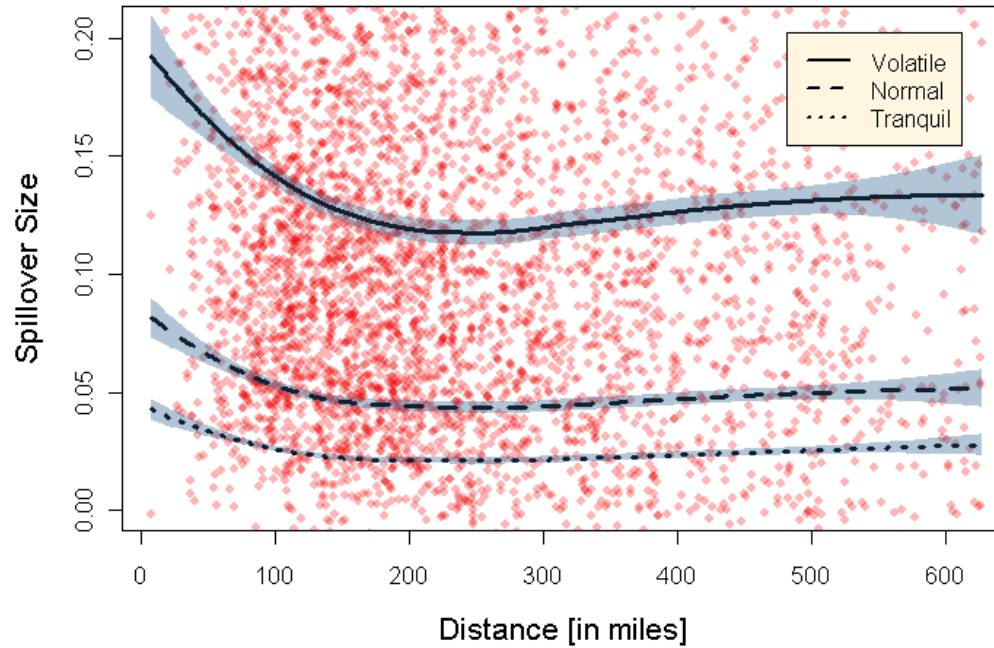


This figure shows in the left graph the geographical distribution of the properties of Essex Property Trust and Kilroy Realty Corporation with properties in very similar locations. The right graph shows the distance between Essex Property Trust and Cogdell Spencer Inc. with a very long distances between their properties.

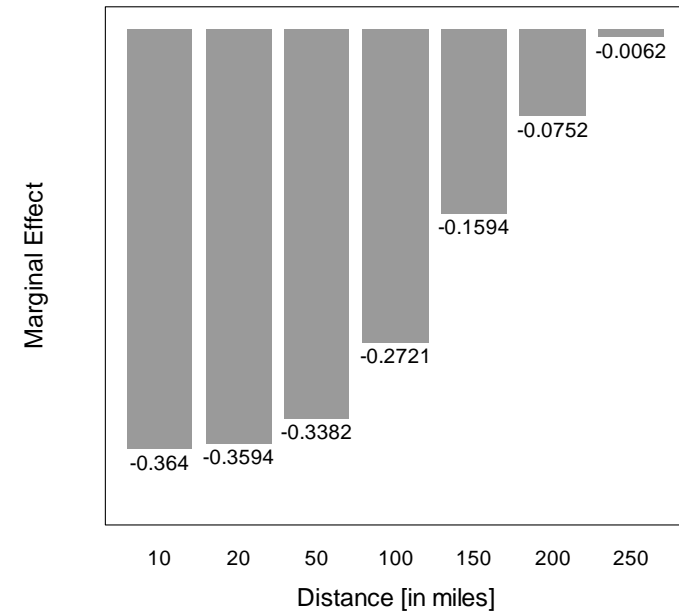
Figure 6: Determinants of Risk Spillover Size

Panel A: Non-Linear Part

Nonparametric Estimate of the Risk Gradient



Marginal Effects during Volatile Markets [%]



Panel B: Linear Part

	Volatile	Normal	Tranquil		Volatile	Normal	Tranquil
<i>Constant</i>	0.0795***	0.0106*	0.0055	<i>Med. Size</i>	0.013***	0.02***	0.0154***
<i>Industrial</i>	0.0356**	0.0006	0.0017	<i>High Size</i>	0.0555***	0.053***	0.0372***
<i>Office</i>	-0.0005	0.0039**	0.0006	<i>Med. MTB</i>	0.0043	0.0126***	0.006**
<i>Residential</i>	0.0186***	0.0196***	0.0131***	<i>High MTB</i>	-0.0006	0.0031	0.0013
<i>Retail</i>	-0.0208***	-0.0167***	-0.0082***	<i>Med. Beta</i>	0.041***	0.0167***	0.007***
<i>Med. Leverage</i>	0.0588***	0.0275***	0.0142***	<i>High Beta</i>	0.0613***	0.0294***	0.0142***

<i>High Leverage</i>	0.0414 ^{***}	0.0224 ^{***}	0.0056 ^{***}	<i>Transmitter F.E.</i>	Yes	Yes	Yes
<i>Med. Mat. Mis.</i>	0.003	0.0087 ^{***}	0.0024 ^{***}	<i>F-Statistic</i>	61.203	53.846	46.806
<i>High. Mat. Mis.</i>	0.0231 ^{***}	-0.0061 ^{***}	-0.0045 ^{***}	<i>Adj. R-Squared</i>	0.529	0.496	0.46

This table shows the coefficients of various balance sheet regressors that enter the model in categorical form. The dependent variable is the spillover coefficient during three financial states (tranquil, normal, and volatile). Panel A presents the estimation results of the non-parametric regression with risk spillovers as a function of distance together with the nonparametric estimate for tranquil, normal, and volatile REIT states. Panel B shows the coefficient estimates of the linear parametric part for the three financial market states. The intercept is the spillover estimate for a small REIT with a diversified sector focus that has low leverage, low maturity mismatch, low MTB, and low market beta and that receives a risk spillover from a REIT with a different property type. Transmitter fixed effects control for relevant characteristics of the REITs on the right hand side from which the risk is propagated to the left hand side of our SDSVaR equation. The total number of observations is 5,402 for each financial state. Estimates for statistical significance are based on a heteroscedasticity-consistent coefficient covariance matrix.

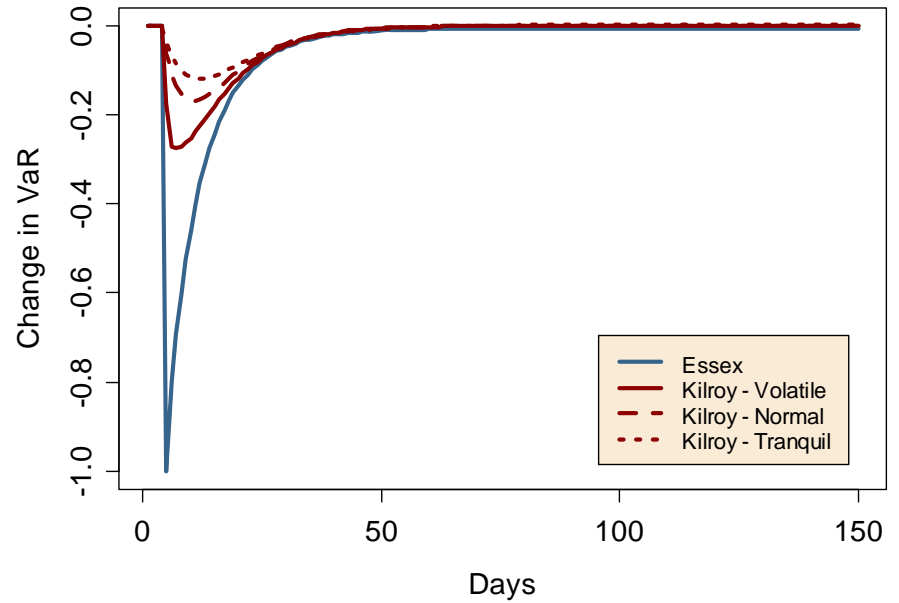
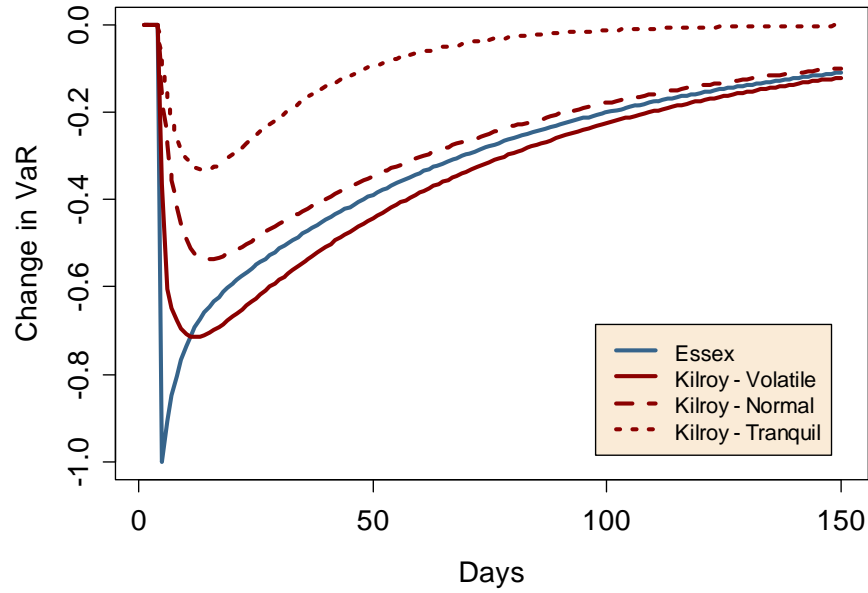
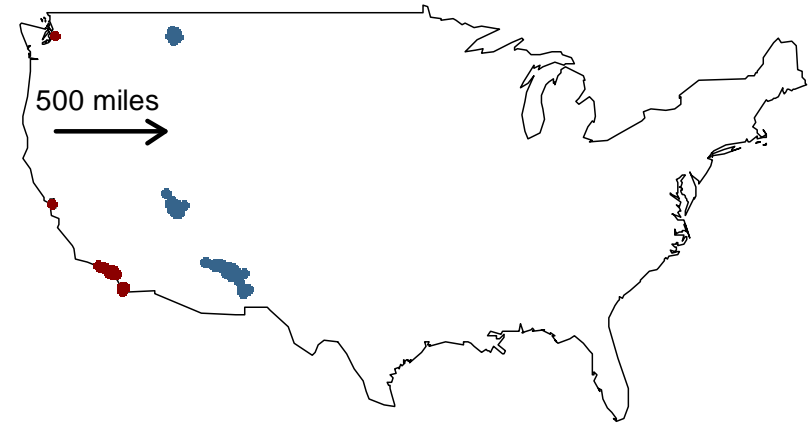
Figure 7: Impulse Response Functions for Close and Distant Properties

Actual Average Distance Among Properties: 9.080 miles

Counterfactual Analysis with Distance set to 500 miles

- Essex Property Trust
- Kilroy Realty Corporation

- Essex Property Trust
- Kilroy Realty Corporation



This figure presents the impulse response functions that demonstrate the dynamic behaviour of a system of two REITs in the presence of a one-time shock to one of the REITs, Essex Property Trust and Kilroy Realty Corp. (upper left graph), for each financial state. The two companies have their properties located in the same regions with an estimated distance of 9 miles. The upper right graph shows a simulation when shifting the properties of Essex Property Trust 500 miles away from their initial location. The lower left graph presents the impulse response functions for the current situation, whereas the lower right graph demonstrates the reaction to a shock in the counterfactual situation.